Big Data and Computing Visions

www.bidacv.com

Big. Data. Comp. Vis. Vol. 1, No. 4 (2021) 170–178.

Paper Type: Original Article

Estimating Cash in Bank Branches by Time Series and Neural Network Approaches

Pejman Peykani [1], Farzad Eshghi [2,*], Alireza Jandaghian [3], Hamed Farrokhi-Asl [4], Farid Tondnevis [5]

[1] Department of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran; pejman.peykani@yahoo.com

[2] Department of Mathematics, Science and Research Branch, Islamic Azad University, Tehran, Iran; eshghise@gmail.com.

[3] Department of Industrial Engineering, K. N. Toosi University of Technology, Tehran, Iran; alirezajandaghian@yahoo.com.

[4] Sheldon B. Lubar School of Business, University of Wisconsin-Milwaukee, Milwaukee, Wisconsin, USA; farrokh5@uwm.edu.

[5] Department of Management, University of Tehran, Tehran, Iran; farid.tondnevis@gmail.com.

Citation:

Peykani, P., Eshghi, F., Jandaghian, A., Farrokhi-Asl, H., & Tondnevis, F. (2021). Estimating cash in bank branches by time series and neural network approaches. *Big data and computing visions, 1* (4), 170-178.

Received: 22/07/2021 Reviewed: 25/08/2021 Revised: 14/09/2021 Accept: 03/10/2021

Abstract

Providing efficient and powerful approach for liquidity management of bank branches has always been one of the most important and challenging issues for researchers and scholars in the banking field. In other words, estimating the amount of required cash in different branches of the bank is one of the basic and important questions for managers of the banking system. Because on the one hand, if the amount of cash is less than the required amount, the bank runs the default risk, and on the other hand, if the amount of cash is more than the required amount, the bank incurs opportunity costs. Therefore, the purpose of this study is to provide a practical approach to predict the optimal amount of required cash in bank branches. For this purpose, the concepts of time series, neural network approach and vector autoregressive model are used. The effectiveness of the proposed approach is also examined using real data.

Keywords: Banking system, Cash prediction, Liquidity requirement, Neural network, Time series.

1 | Introduction

Banks act as the backbone of the financial system in money market-based economic systems. These institutions actually act as intermediaries in the economy. In other words, they collect financial resources from sectors of the economy that have surplus cash and allocate them to sectors of the economy that need funds for investment. This process is reflected in the bank balance sheet. In fact, the balance sheet shows the amount and combination of financial resources that have entered the bank and the resources that have been absorbed, to perform what combination of financing activities (such as providing facilities, investing in projects and companies, investing) in other securities (financial and non-financial institutions) are used. A bank's balance sheet is in optimal condition if it can meet the following three conditions simultaneously [1] and [2]:

Corresponding Author: eshghise@gmail.com

10.22105/bdcv.2021.142232

I. The bank must be able to absorb all possible losses without compromising the rights of creditors (financiers including shareholders and depositors). In other words, the higher the amount of equity and the lower the probability of a decrease in the market value of the bank's assets relative to the value of the debts, leads to the creation of stable and acceptable conditions in the bank.

II. The bank must be able to respond quickly to all requests for cash, both in normal and critical situations. In other words, the bank must be able to meet the needs of depositors who want to withdraw their funds from the bank at any time. In the short run, this depends on the liquidity reserves in the bank and, at the same time, on the use of efficient monitoring systems that are able to predict the unexpected outflow of cash in the bank.

III. The bank must be able to maintain a stable balance in the time horizon between long-term and long-term cash inflows and outflows. Establishing this depends on the degree of compliance and coordination in the weighted average maturity of the bank's assets and liabilities.

Accordingly, the capital regulations of banks, which are formulated and submitted by the Basel banking supervision committee, seek to provide guidelines for the implementation of the above three principles in the banking system. These requirements follow the measurement of the risk level of balance sheet and off-balance sheet activities of banks and determine the amount of capital required to limit the probability of default of the bank at the desired confidence levels. According to the simple proposed approach in the Basel I, the amount of capital required to finance loans is at least equal to 8% of the bank's risk-weighted assets. At the same time, this approach considers the amount of credit risk of each asset in calculating risk-weighted assets [3].

The Basel II provide a more sophisticated yet efficient approach to credit risk calculations. This framework is based on the three pillars of capital regulation, regulatory oversight and information disclosure. The first pillar examines the amount of capital required to cover credit losses at the 99.9% confidence level. At the same time, the degree of diversification of credit risk in the second pillar is assessed by the regulator, which has the ability to adjust capital adequacy requirements. Although Basel II Capital Regulations also cover operational and market risks, its focus is on credit risk as a major cause of adverse events in the banking industry [4].

During the financial crisis of 2007-2009, many banks faced problems due to lack of liquidity due to the tendency of depositors to withdraw their cash from banks. Vulnerable banks financed their long-term assets from short-term sources and as a result were unable to meet the needs of depositors. In response to this crisis, the Basel committee, focusing on liquidity risk as one of the most important factors influencing the banking system, introduced its new guidelines to increase the ability of banks to absorb shocks and, consequently, greater flexibility in the face of possible future crises. The principles of the internal approach to credit risk management presented by Basel II have remained unchanged in Basel III. In other words, the risk-weighted weighting of assets, in order to create a more flexible banking system, is associated in Basel III with higher capital ratios and greater emphasis on tier I capital [5].

Liquidity in financial markets has different definitions and applications. In general, liquidity management indicates the ability to strike a stable balance between cash inflows and outflows over time. Undoubtedly, liquidity management has a more rigorous structure for banks due to their functional nature (funds intermediation). The limitations of liquidity risk management mentioned in Basel III are: the ratio of liquidity coverage and the net ratio of sustainable resources. The liquidity coverage ratio ensures that there is a portfolio of high-quality liquid assets in the bank that can meet the cash outflow needs in the next 30 days. In other words, this ratio examines the short-term access of the bank to cash resources. The net ratio of fixed resources also examines the financing of banks' assets and long-term activities by considering the minimum acceptable sustainable sources and considering the liquidity of bank assets over a longer period of time.

Zaragoza and Mota [6] examined cash liquidity optimization methods in bank branches. Baghbani and Eskandari [7] used Bayesian data mining approach to calculate the required cash in bank branches. Bilir and Döşeyen [8] attepted to optimize Automated Teller Machines (ATM) and branch cash operations by applying an integrated cash requirement forecasting and cash optimization model. Lázaro et al. [9] improved cash logistics in bank branches by utilizing machine learning and Robust Optimization (RO) approaches. Tavana et al. [10] applied Artificial Neural Network (ANN) and bayesian network model to assess liquidity risk in banking. Desai et al. [11] examined operational ATM and optimization of cash liquidity management by employing mobile application. Ranjbarfard and Ahmadi [12] surveyed on data requirements for applications of data mining in banking industry.

According to the explanations, undoubtedly, the liquidity management of the branches is of great importance among the managers of the banking system. In other words, how much cash resources each branch should have in order to meet the needs of customers in the coming month, is one of the most important concerns and questions in the field of banking. Therefore, the purpose of this study is to present and implement an efficient approach to estimate the optimal amount of cash required in bank branches. Notably, two different forecasting methods based on time series and neural network are used.

2 | Proposed Approach

Liquidity management is always one of the most important and challenging issues facing the banking system [13]. In other words, estimating the adequacy of cash required in different branches of the bank in order to respond to clients and owners of deposits, is always one of the basic questions for managers of the banking system. On the one hand, if the amount of cash in the bank is less than the bank needs to respond to clients, the requests of some customers will be delayed, which is unacceptable, and leads to dissatisfaction of customers and depositors of the bank. On the other hand, if this amount is too sufficient, the bank will incur significant opportunity costs. Because the excess amount of these funds could be used in various investments, granting facilities, etc. In addition, keeping large amounts of cash in the bank can increase the risk of damage resulting from the loss of all or part of the cash due to natural disasters, fires, armed robbery, etc. from the bank. In short, each branch must be able to strike a long-term, stable balance between the inflow and outflow of its cash. Creating such a balance requires predicting the amount of cash inflows and outflows of the branch.

Peykani et al.| Big. Data. Comp. Vis. 1(4) (2021) 174-182

In order to predict the optimal amount of cash required in bank branches, basic methods or statistical methods can be used. In the basic methods, the behavior and characteristics of the real and legal personalities of the bank depositor are analyzed and the probability of their deposit being withdrawn for the next period is calculated. But in statistical methods, past information is the basis for predicting future events. The main structure of the proposed approach is based on topics related to time series, neural network and vector autocorrelation model, the steps of which are summarized as follows:

Step 1. In the first step, the cash inflow and outflow data are extracted along with the ATM withdrawals and placed in independent tables, with dates in rows and branches in columns. In other words, each column in each table represents the desired time series for specific branches.

Step 2. The total cash inflows and outflows from the ATM are calculated for each date. In other words, the result of this step is the creation of three independent time series that show how much cash inflows, cash outflows and ATM withdrawals have been for each branch per day.

Step 3. The significance of all three time series of cash inputs, cash outputs and ATM withdrawals are checked using two functions of autocorrelation and partial autocorrelation. It should be noted that if the distribution of a random variable remains unchanged over time, the series in question remains constant.

Step 4. The future values of these three time series are predicted using linear models. In other words, the total amount of cash entering and leaving the bank and the total withdrawals from ATMs for the next 30 days are forecast.

Step 5. The share of each branch is calculated from 3 variables: cash inflow, cash outflow and withdrawal from ATM over time. The result of this step is 100 independent time series that show what proportion each branch allocates to cash inflows, outflows and ATM withdrawals at each date.

Step 6. Then the time series of cash inflows, cash outflows and withdrawals from the ATM created in the previous step, using the neural network approach and the vector autocorrelation model, are predicted for the next 30 days.

Step 7. Finally, using the output and results of steps 4 and 6, the amount of cash inflows, cash outflows and withdrawals from the ATM in each branch for the next 30 days are calculated.

3 | Implementation and Experimental Results

In order to implement the proposed research approach, cash input and output data of 100 branches along with information about withdrawals from ATMs of these branches, for a period of 3 consecutive years for one of the banks operating in Iran has been used. The purpose of implementing the proposed research approach is to predict the values of these three variables including cash inputs, cash outputs and withdrawals from ATMs over the next 30 days for each of the 100 branches as a case study. It is necessary to explain that in this research and in order to implement the proposed approach, MATLAB software has been used. Based on this, the following explains how to implement the research approach using real data. In the first step, as mentioned in the previous section, the required data is extracted and processed. Then, the meaning of the mentioned time series should be examined. Based on this and as an example, the time series diagram of the total cash inflow is drawn as *Fig. 1*:

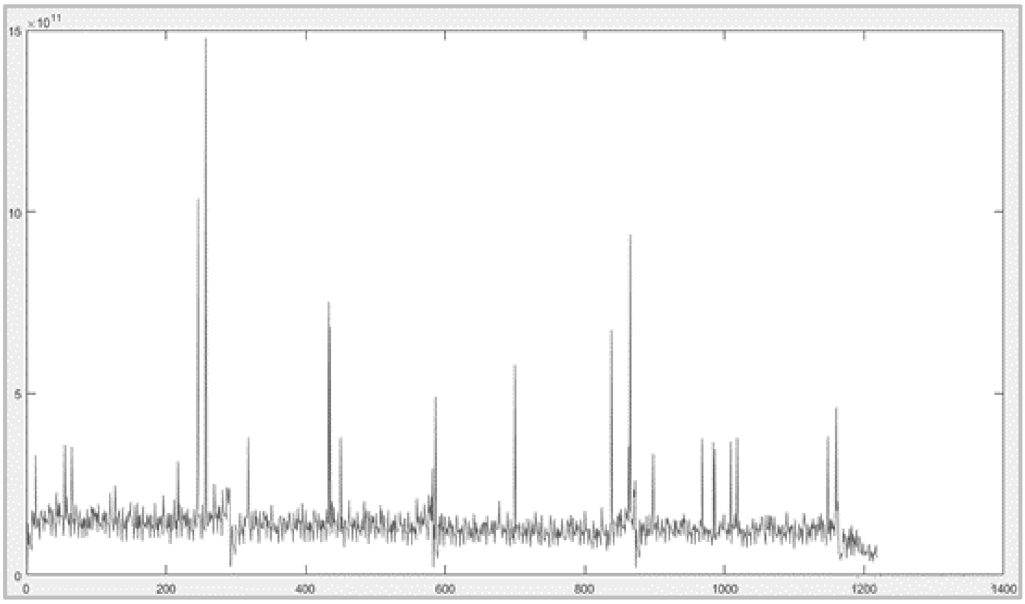

Fig. 1. Time series diagram of the total inflow of the bank.

It should be noted that if a time series is constant, its autocorrelation value will diminish with increasing time intervals, in other words, it will be close to zero. Therefore, the future behavior of such time series can be modeled using its past values linearly. In order to investigate the significance of the mentioned time series, the two functions of autocorrelation and partial autocorrelation of the total time series of cash inflows are examined, the corresponding diagrams of which are shown in *Fig. 2*:

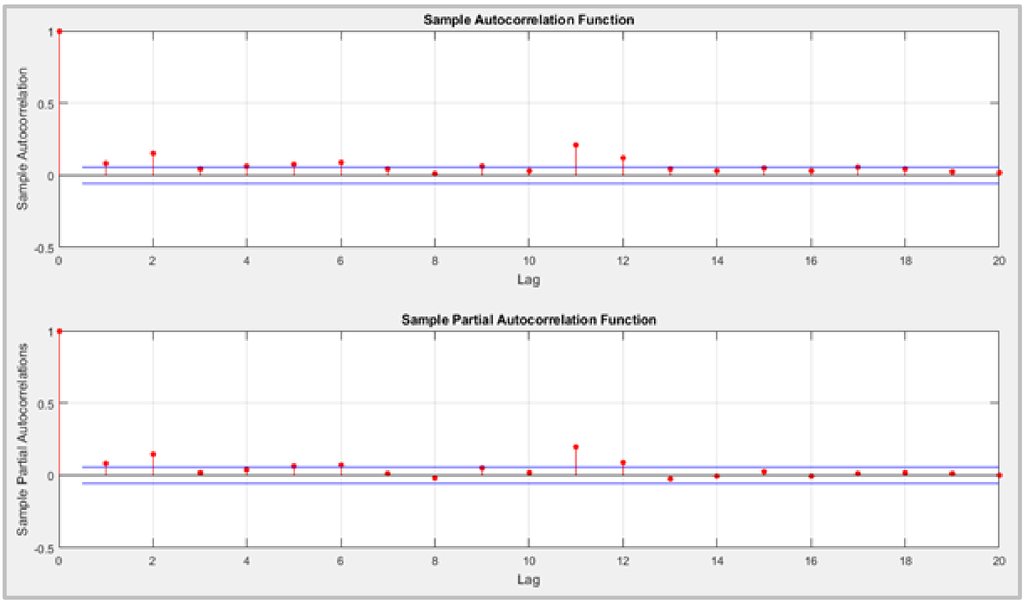

Fig. 2. Chart of self-correlation and partial self-correlation.

According to *Fig. 2*, the value of autocorrelation and partial autocorrelation will be damp after 11 breaks. Hence the ARIMA (11,0,11) model explains this time series. Also, residuals values should be analyzed to check the accuracy of the model. It should be noted that the residuals should have a normal distribution and zero autocorrelation and partial autocorrelation. the results of which are presented below:

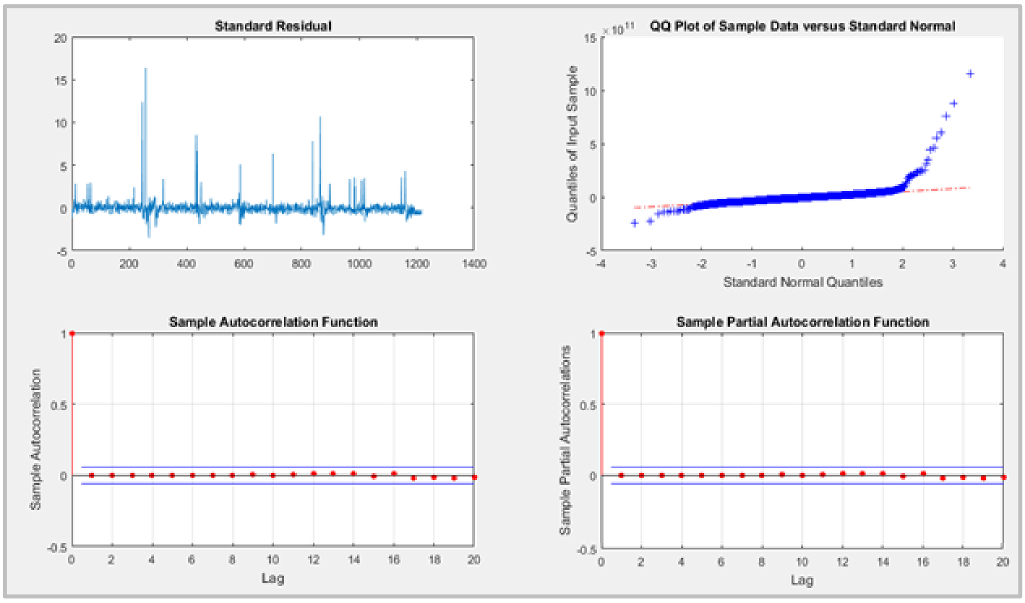

Fig. 3. Analysis of residuals values.

As can be seen in the diagrams above, the residuals have a normal distribution and zero autocorrelation and partial autocorrelation. Therefore, it is possible to use the mentioned model to predict future periods. It should be noted that the above steps have been performed for the other two time series, namely cash outputs and withdrawals from ATMs. Then, the total amount of cash inflows to the bank and the outflow of cash from the bank along with the total amount of withdrawals from ATMs for the next 30 days are forecasted. Next, the share of each branch in the inflow and outflow of cash and withdrawals from bank ATMs using the neural network and its vector correlation model is predicted. It should be noted that neural network is one of the most widely used and common techniques in the field of data mining for estimation and prediction [14].

In general, neural networks have different applications such as data classification, approximation of functions, prediction of variables, clustering and optimization. To use the neural network approach to predict in the present study, 100 time series for each of the three variables, including cash inputs, cash outputs and ATM withdrawals, are considered as model inputs. Now, by applying the ntstool command, the neural network time series window in MATLAB software is as follows:

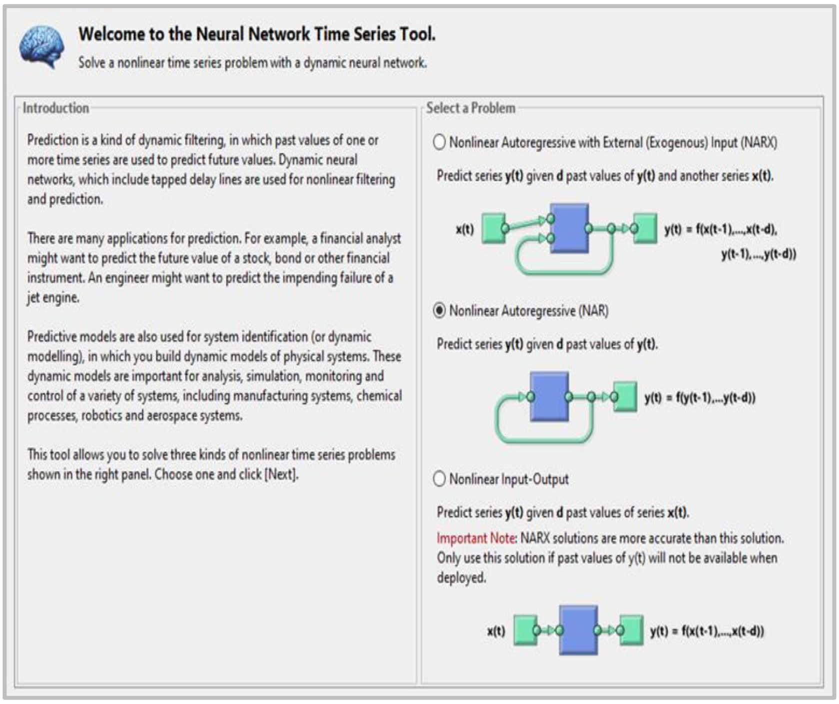

Fig. 4. The initial window of neural network implementation in MATLAB software.

According to the purpose of the analysis, the Nonlinear Autoregressive option is selected and the variable X is considered as input:

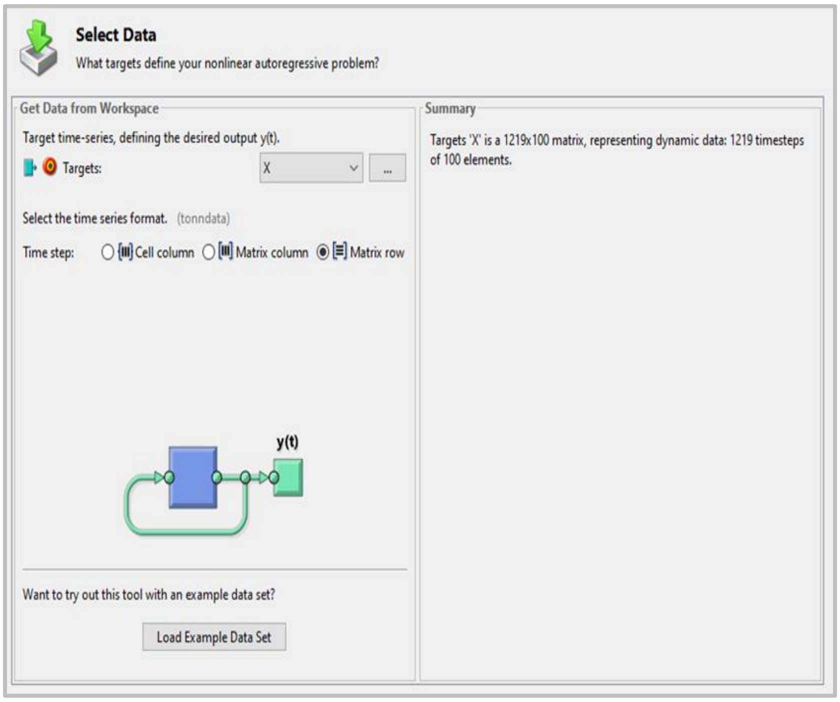

Fig. 5. The window of data selection to run the neural network in MATLAB software.

Peykani et al. | Big. Data. Comp. Vis. 1(4) (2021) 174-182

In the next step, 5 layers and 4 interrupts are considered for neural network training:

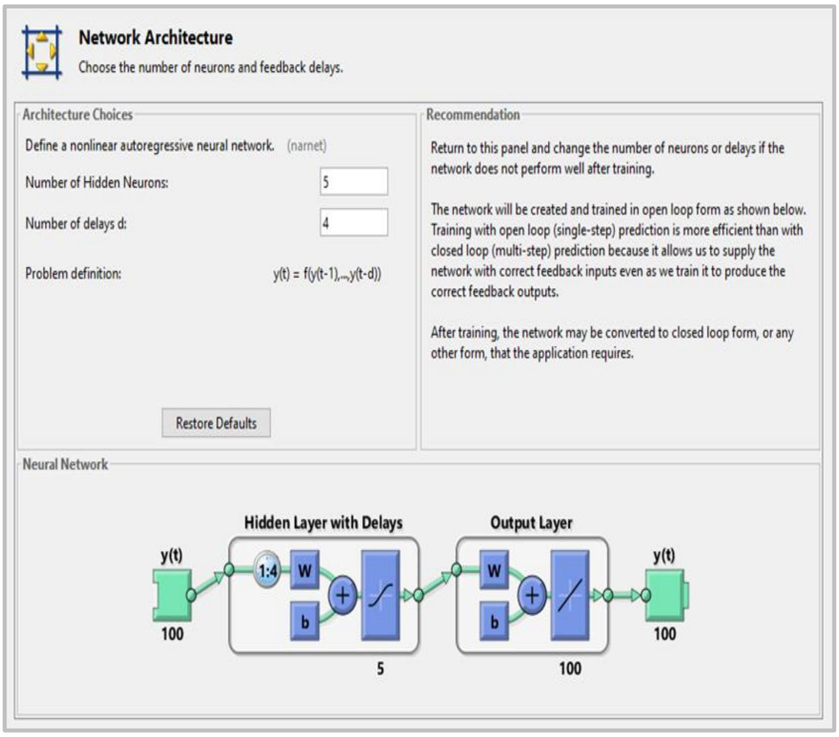

Fig. 6. The window of architecture design of the neural network in MATLAB software.

After setting layers and interrupts parameters, the neural network is trained using data and the Scald Conjugate Gradient algorithm:

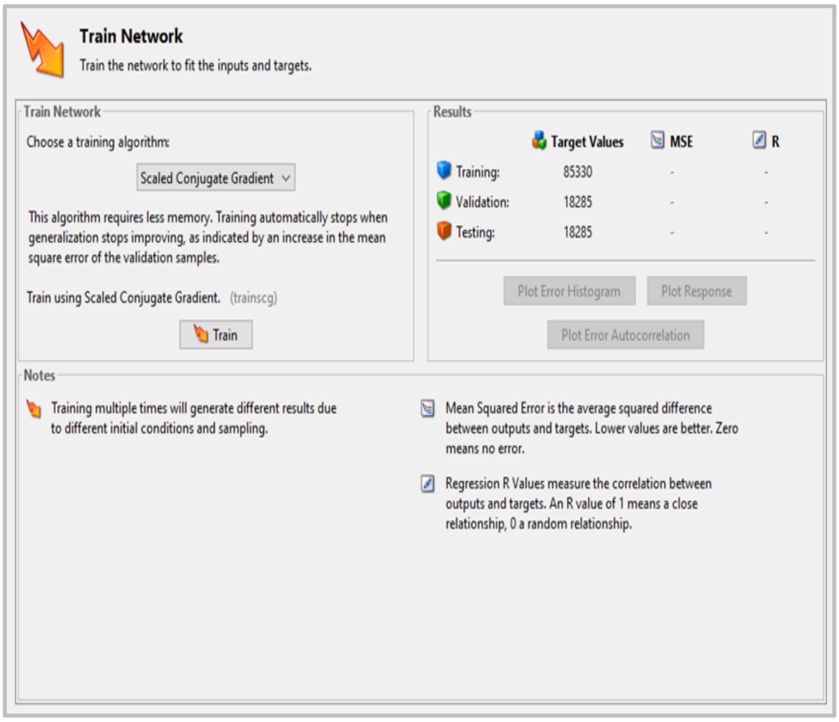

Fig. 7. The window of training of the neural network in MATLAB software.

The training results are saved and then predicted for the next 30 periods by employing the created neural network:

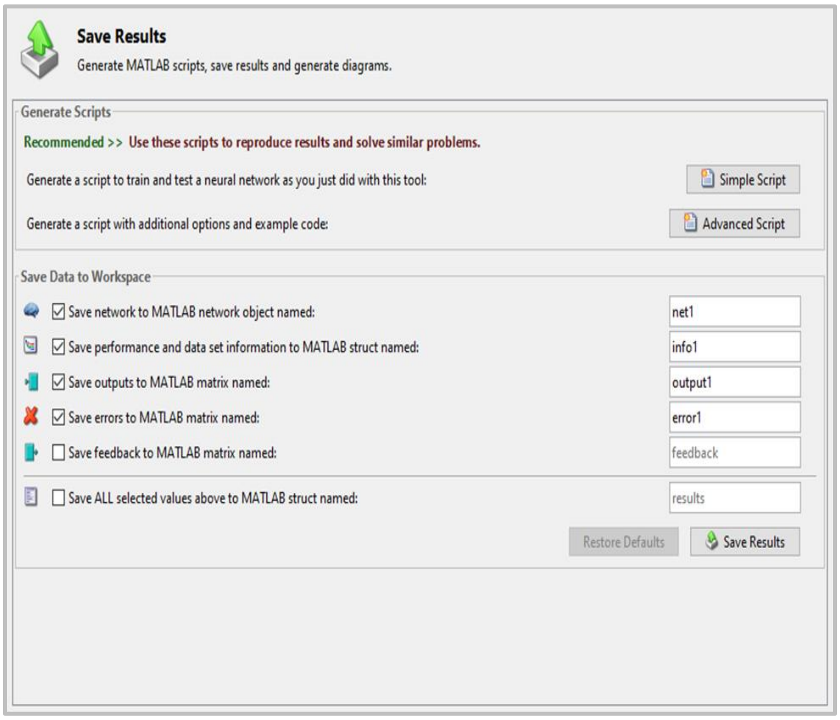

Fig. 8. The final window of neural network execution in MATLAB software.

It should be noted that all the above steps are implemented for all 3 variables of the research, including cash inflows, cash outflows and withdrawals from ATMs, and finally the required amounts of cash in each of the bank branches are calculated.

4 | Conclusions and Future Research Directions

Estimating and calculating the amount of cash required in different branches of the bank is always one of the most important and challenging issues for the managers of the banking system. Therefore, in this study, an attempt was made to provide an efficient method for estimating the optimal amount of cash in bank branches by using the concepts of time series, neural network approach and autocorrelation model. Also, how to implement the proposed research approach operationally, using real data extracted from 100 bank branches, was implemented and reviewed. Finally, for future studies, it is suggested that the Data Envelopment Analysis (DEA) approach is used to classify and rank bank branches based on their liquidity management, and according to the results, efficient branches are considred as benchmark for inefficient branches [15]-[18]. Also, using uncertainty programming approaches such as fuzzy optimization and robust optimization, the effect of uncertainty in the data in the forecasting process can be considered [19]-[25].

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Santos, J. A. (2001). Bank capital regulation in contemporary banking theory: a review of the literature. *Financial markets, institutions & instruments*, *10*(2), 41-84.

[2] Demyanyk, Y., & Hasan, I. (2010). Financial crises and bank failures: a review of prediction methods. *Omega*, *38*(5), 315-324.

[3] Balthazar, L. (2006). *From Basel 1 to Basel 3: The integration of state-of-the-art risk modelling in banking regulation*. Springer.

[4] Herring, R. J. (2002). The basel 2 approach to bank operational risk: regulation on the wrong track. *The journal of risk finance*, *4*(1), 42-45.

[5] King, P., & Tarbert, H. (2011). Basel III: an overview. *Banking & financial services policy report*, *30*(5), 1-18.

[6] Zaragoza, M. A., & Mota, I. F. D. L. (2016). Tactics for approaching cash optimisation in bank branches. *International journal of simulation and process modelling*, *11*(6), 492-503.

[7] Baghbani, G., & Eskandari, F. (2018). Calculating the required cash in bank branches: a Bayesian-data mining approach. *Neural computing and applications*, *30*(9), 2831-2841.

[8] Bilir, C., & Döşeyen, A. (2018). Optimization of ATM and branch cash operations using an integrated cash requirement forecasting and cash optimization model. *Business & management studies: an international journal*, *6*(1), 237-255.

[9] Lázaro, J. L., Jiménez, Á. B., & Takeda, A. (2018). Improving cash logistics in bank branches by coupling machine learning and robust optimization. *Expert systems with applications*, *92*, 236-255.

[10] Tavana, M., Abtahi, A. R., Di Caprio, D., & Poortarigh, M. (2018). An Artificial Neural Network and Bayesian Network model for liquidity risk assessment in banking. *Neurocomputing*, *275*, 2525-2554.

[11] Desai, A. P., Bobade, S. R., Baravkar, K. K., Nerkar, Y. A., Ankleshwar, M., & Navale, M. P. (2019). A survey on identifying operational ATM and optimization of cash management using mobile app. *International journal of innovative science and research technology*, *4*(1), 279-281.

[12] Ranjbarfard, M., & Ahmadi, S. (2020). A study of data requirements for data mining applications in banking. *Journal of Digital Information Management*, *18*(3), 109-117.

[13] Cabello, J. G. (2013). Cash efficiency for bank branches. *Springer Plus*, *2*(1), 1-15.

[14] Tam, K. Y. (1991). Neural network models and the prediction of bank bankruptcy. *Omega*, *19*(5), 429-445.

[15] Charnes, A., Cooper, W., Lewin, A. Y., & Seiford, L. M. (1997). Data envelopment analysis theory, methodology and applications. *Journal of the operational research society*, *48*(3), 332-333.

[16] Emrouznejad, A., & Yang, G. L. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-economic planning sciences*, *61*, 4-8.

[17] An, Q., Tao, X., & Xiong, B. (2021). Benchmarking with data envelopment analysis: an agency perspective. *Omega*, *101*, 102235. https://doi.org/10.1016/j.omega.2020.102235

[18] Peykani, P., Farzipoor Saen, R., Seyed Esmaeili, F. S., & Gheidar-Kheljani, J. (2021). Window data envelopment analysis approach: a review and bibliometric analysis. *Expert systems*, *38*(7), e12721. https://doi.org/10.1111/exsy.12721

[19] Olesen, O. B., & Petersen, N. C. (2016). Stochastic data envelopment analysis—a review. *European journal of operational research*, *251*(1), 2-21.

[20] Peykani, P., Mohammadi, E., Saen, R. F., Sadjadi, S. J., & Rostamy-Malkhalifeh, M. (2020). Data envelopment analysis and robust optimization: a review. *Expert systems*, *37*(4), e12534. https://doi.org/10.1111/exsy.12534

[21] Peykani, P., Mohammadi, E., Jabbarzadeh, A., Rostamy-Malkhalifeh, M., & Pishvaee, M. S. (2020). A novel two-phase robust portfolio selection and optimization approach under uncertainty: a case study of Tehran stock exchange. *Plos one*, *15*(10), e0239810.

[22] Banker, R. D. (2021). Stochastic data envelopment analysis. *Data envelopment analysis journal*, *5*(2), 281-309.

[23] Peykani, P., Mohammadi, E., & Emrouznejad, A. (2021). An adjustable fuzzy chance-constrained network DEA approach with application to ranking investment firms. *Expert systems with applications*, *166*, 113938.

[24] Peykani, P., Hosseinzadeh Lotfi, F., Sadjadi, S. J., Ebrahimnejad, A., & Mohammadi, E. (2021). Fuzzy chance-constrained data envelopment analysis: a structured literature review, current trends, and future directions. *Fuzzy optimization and decision making*, 1-65. https://link.springer.com/article/10.1007/s10700-021-09364-x

[25] Zahedi-Seresht, M., Khosravi, S., Jablonsky, J., & Zykova, P. (2021). A data envelopment analysis model for performance evaluation and ranking of DMUs with alternative scenarios. *Computers & industrial engineering*, *152*, 107002. https://doi.org/10.1016/j.cie.2020.107002